

Real-Time IoT-based Power Generation Forecasting in Microgrid System

Narendra Babu P^{1†} and Dadinaboina Anantha Koteswara Rao², Non-members

ABSTRACT

A microgrid network is a small scale electrical grid network which is used to generate electrical power from various renewable energy resources such as wind energy and solar energy to provide reliable and consistent power to the local customer. Wind energy and solar energy are both weather dependent renewable resource due to this intermittence power generation occur and unstable quality power generation cause voltage fluctuation between point of common coupling and load in microgrid system. Therefore in order to supply high quality sufficient, consistent, and stable power to critical loads it is mandatory to study on accurate power forecasting in microgrid system. Power outages power in microgrid vary the power consumption and affect electrical tariff and changes human behaviour in response to the changes in electrical tariff. The intermittence and uncertainty renewable energy may cause unstable quality power generation in microgrid. The paper presents the combined ETS model with ARIMA-SARIMA technique for power forecasting in microgrid systems. Moreover, real-time power quality characteristics are also presented in the paper.

Keywords: Microgrid, distribution generation, power forecasting, PV system, IoT

1. INTRODUCTION

Primary power grids consist of a complex fabric of generation plants, substations and transmission lines that help supply electricity to cities, homes, and small businesses. In a conventional grid energy may come from a variety of sources, such as coal hydroelectric plants and nuclear energy. In addition to primary power grids there exists smaller independent grids called microgrids. These microgrids provide power to remote areas. A power grid system that incorporates microgrids would still have conventional centralized energy sources, but

many more users would have local sources of energy [1].

In a utility grid network that incorporates microgrids, the microgrid can coordinate the use of local energy sources. This allows local power grids to maintain necessary levels of service, operating independently from the larger grid, so users may continue to receive power even after a blackout occurs. In a conventional power grid, a blackout at the utility company substation would cause all users to lose power. A microgrid can separate itself from the main grid during unscheduled periods of electricity interruption to continue feeding its own islanded portion of the grid. In addition, microgrid users can independently manage and distribute home-grown energy, since these sources are distributed locally within the microgrid. Microgrids include the integration and control of multiple local generation and storage devices, such as diesel generators, and battery systems. This provides on-site generation for local loads in both grid-tied and islanded modes of operation [2].

In addition to these conventional generation sources, microgrids also incorporate the use of renewable energy such as wind turbines and solar panels (PV). This helps reduce the dependency on conventional fossil fuel, while at the same time reducing carbon dioxide (CO₂) emissions. The drawback of incorporating these renewable energy sources is in their dependency on variable natural resources. The variability of renewable energy sources requires quick response from the microgrid and highly efficient storage devices to ensure stability. For this reason, it is necessary for microgrids to have the ability to forecast wind and solar behaviour to estimate the electricity production during the day [3–5]. This paper focuses on a prediction model for solar irradiance forecasting. The proposed forecasting method model's historical data as a time series to predict solar irradiance behaviour. The proposed solar irradiance prediction model is tested using a residential microgrid model.

Energy forecasting has come to be a common concern among research due to the cumulative impact of renewable energy in the present-day power system. The most common RESs are wind, water, solar and biofuel or biomass. The customary utilization of these energy sources includes power generation, heating, and transport fuels. Renewable energy sources are of importance because of their capacity to sustain [6]. This outcome is a substitute for the diminution of conventional energy sources for example coal, petrol, and nuclear energy. Energy from these sources is clean and has a much lower environmental impact when compared to traditional energy sources. As a result of the impact, it is vital

Manuscript received on November 24, 2024; revised on December 7, 2025; accepted on May 26, 2026. This paper was recommended by Associate Editor Komsan Hongesombut.

¹The author is with the School of Electrical & Electronics Engineering (SEEE), VIT Bhopal University, Kothrikalan, Sehore-466114, Madhya Pradesh, India.

²The author is with SRKR Engineering College, Bhimavaram, AP, India.

[†]Corresponding author: narendrababup204@gmail.com

©2026 Author(s). This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 4.0 License. To view a copy of this license visit: <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

Digital Object Identifier: 10.37936/ecti-ec.2026243.256831

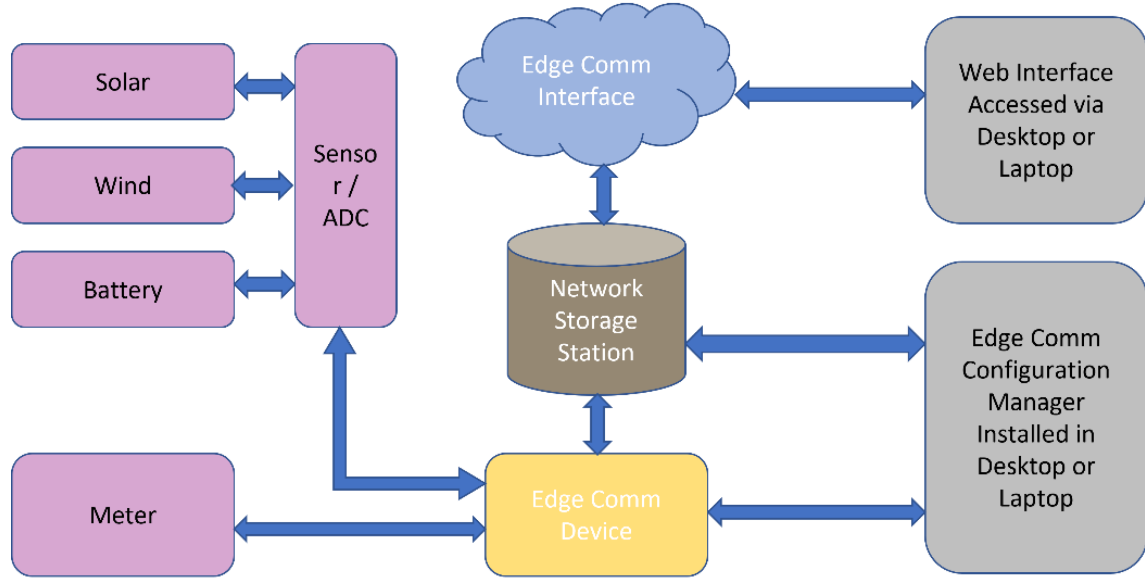


Fig. 1: Generalized block diagram of the proposed system.

for grid workers and stakeholders to ascertain how much power renewable energy sources will yield in the succeeding hours and days. A distributed microgrid system is a less expensive option for the construction of large, central power plants and High-Voltage transmission lines. They afford consumers the potential for lower cost, higher service reliability, high power quality, increased energy efficiency, and energy independence. The use of renewable distributed energy such as wind, photo-voltaic, geothermal, hydroelectric power can also provide a significant environmental benefit [7].

This research, therefore, presents a method for short term energy forecasting in Distributed renewable energy source (D-RES) micro-grids using mobile devices at the network edge. This ensures effective and efficient management of the generated power from micro-grids. Also, these mobile devices have the required storage and network resources to avoid delay-sensitive tasks.

Research in used mobile devices to formulate an IoT architecture that can execute complex computational tasks at the network edge. Mobile devices, however, could be any electronic devices capable of running complicated programming constructs using the medium to low power computational resources. Examples of such devices include micro-controllers, smartphones, and desktop/laptop computers [8]. Generally, energy forecasting for D-RES is done for the effective coordination of power from the grid to the consumers and for scheduling the operation of the different types of Renewable Energy sources in the micro-grid. This research, however, considers the use of energy forecasting for the latter [9]. This is because RESs operate on different mechanisms and with proper coordination and management; they can be made to support each other thus providing a sustainable source of power for distribution to consumers. A well-

defined Electrical topology is therefore proposed in this research that allows for the easy incorporation of RESs into a micro-grid in a distributed fashion. As opposed to the other approaches, this ensures the addition of any number of RES into the DRES network which in turn eliminates the limit to the power that could be generated from the micro-grid. However, as stated in the above paragraph, the mobile devices provide control for the RESs in the D-RES network at the network edge [10].

A wireless sensor network (WSN) is employed to gather data (generated electrical energy) from the D-RES network and passed to the local mobile device for administering the control by using pre-defined control algorithms. With this approach, the appropriate control operation would be administered without delay since operations are carried out at the network periphery. Moreover, external updates would be easily administered with little or no stress on the network bandwidth as the data from the sensors are analysed locally on mobile devices. However, the cloud would be used as a support for the mobile devices by providing permanent storage for the locally generated data and a platform for offloading resource-intensive computations [11]. Nevertheless, mobile devices are constrained by limited computational resources such as memory and processing power. Therefore, the method for energy forecasting should be carefully selected to work with these constraints while still maintaining acceptable accuracy. This research, therefore, utilizes the method of Deep Neural Network (DNN) for creating lightweight machine learning models that can be easily deployed on the resource-constrained devices at the network periphery. DNNs are simply Artificial Neural Networks (ANNs) with a higher number of hidden layers in their architectures [12]. They are well known for their ability to capture

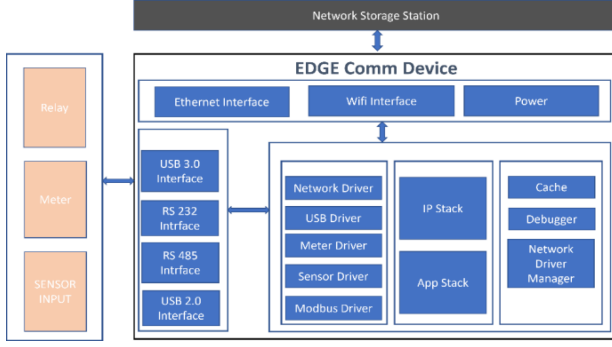


Fig. 2: EDGE Comm controller.

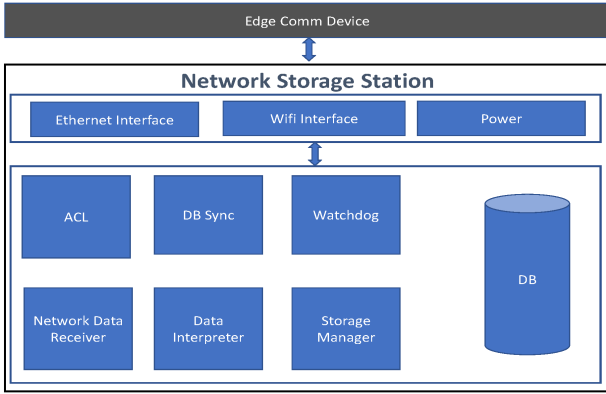


Fig. 3: Workstation.

complex relationships between features of very large non-linear datasets. This approach is used instead of the very old shallow learning method which has fewer hidden layers or the LSTM-based RNN methods which require a huge amount of memory-bandwidth during its operation. The dataset for forecasting energy in the micro-grid is historical data of its generated power. Other researchers consider the use of meteorological data obtained from meteorology stations with special considerations to changes in atmospheric features such as humidity, temperature, light, etc. Even though results obtained with such a dataset are good, the data is not always available for use and as such cannot be relied on [13].

This research would focus on creating the electrical network topology for incorporating the RESs into the micro-grid network with a clear description of the different components and sections. Furthermore, a dataset from a solar power generation company in Belgium would be used to create a DNN model that can be deployed on any mobile device at the network edge. However, the model would be tested with a test dataset to observe for over fitting. Evaluation matrices such as the mean square error (MSE) and the r-square would be used to evaluate the model. Also, the model would be tested with different topologies (number of hidden layers and activation functions) to determine the optimal architecture for the DNN in the D-RES [14–18].

2. SYSTEM DESCRIPTION

Remote monitoring and controlling of the sub-station equipment is an important issue for the power/energy management department which is normally done manually, or using an expensive PLC and SCADA system. With the emergence of the internet and computational era, a smart monitoring and reliable controlling system over the entire sub-station equipment is highly desirable that can be achieved by introducing the Internet of Things (IoT) technology.

The IoT based system allows objects to be sensed or controlled remotely across existing network infrastructure, creating opportunities for more direct integration of the physical world into computer-based systems and resulting in improved efficiency, accuracy and economic benefit with the added merits of minimum human intervention.

3. ENERGY FORECASTING

Accurate forecasting approaches are required to address issues such as supply-demand balance, intermittent nature, and reliability concerns when integrating renewable energy sources (RESs) into the global electric energy system [9]. Figs. 2 and 3 show the EDGE comm controller and work station of the proposed system. To improve the accuracy of forecasts, a range of technologies are used, such as hybrid approaches, statistical techniques, physical models and artificial intelligence systems [9, ?].

As essential components of smart grids, Microgrids are crucial for improving grid stability and localizing power generation. However, the unpredictability of electricity demand and the fluctuating nature of renewable energy sources pose serious obstacles to the stability and reliability of Microgrids. To overcome these challenges, accurate forecasting of energy demand and electricity production from renewable energy sources is required [11]. This enables microgrid operators to make informed decisions regarding energy storage planning, unit bonding and energy trading with commercial grids. Precise predictions increase efficiency, reduce disruptions and make optimal use of available resources. As forecasting tools continue to evolve, we are moving closer to the day when economies, industries and communities are powered primarily by renewable energy sources. Fig. 5 shows the power forecast data flow in the proposed system.

Figure 5 depicts the data flow for energy forecasting, which is divided into three key components: import dataset, processing and visualization, and model building. Import Data simply takes in the appropriate feature and Time-Date Object, which is represented as an index and the feature represents its relevant values. Because we're dealing with time series, it needs to be univariant. Then, in preprocessing and visualization, we execute preprocessing procedures or filtering data based on demands by visualizing them since visualization provides more generalized outcomes than value representation or score, allowing us to discover where we are falling

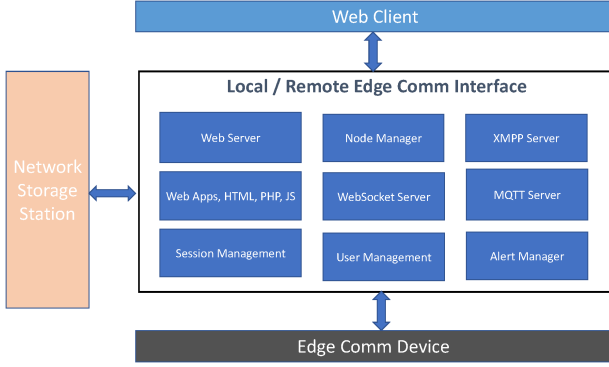


Fig. 4: Overall functional blocks.

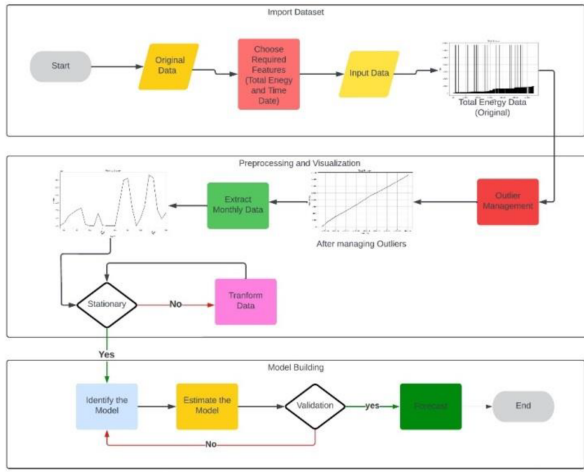


Fig. 5: Energy Forecast Data Flow Diagram.

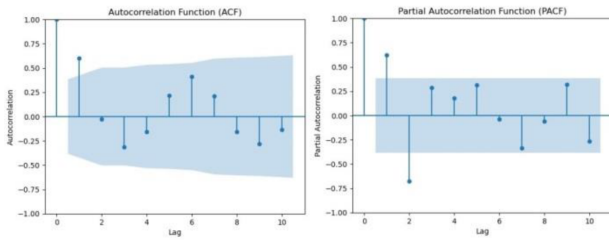


Fig. 6: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Graphs for energy forecasting.

behind. Finally, we will build the model by identifying, transforming, and estimating it till we receive validation.

3.1 ARIMA technique

As an extension of the ARMA model, the Auto Regression Integrated Moving Average model (ARIMA) uses integration to eliminate non-stationary and estimate random probability distributions [12]. Lags of the original series and/or lags of forecast errors are also used as a regressor, which is why we can call it a regression.

Suppose that S represents original time series, S_{t-j} represents the lag j series, and ϵ_{t-j} represents the lag j

forecast errors. Then:

$$S_t = c + \sum_{j=1}^p \vartheta_j S_{t-j} + \sum_{j=1}^q \theta_j \epsilon_{t-j}, \quad (1)$$

where c is a constant, ϑ_j represents coefficient for autoregression term, θ_j represents the moving average coefficient and p and q represent orders used to determine the number of coefficients.

Since the value of covariance between two observations is based only on lags or we only have two parameters (p and q) for the above, we intend to do appropriate preprocessing when using the above approach for non stationary.

The ARIMA(p, d, q) model is expressed with the backward operator $\beta S_t = S_{t-1}$, which gives the difference. The non-stationarity is by integration (difference) as follows:

$$\vartheta_p(\beta)(1 - \beta)^d S_t = \theta_q(\beta)\epsilon_t \quad (2)$$

Above $\vartheta_p(\beta) = 1 - \sum_{j=1}^p \vartheta_j \beta^j$ represents the autoregression operator and $\theta_q(\beta) = 1 - \sum_{j=1}^q \theta_j \beta^j$ represents the moving average operator, these two are the back-shift operators represented as a polynomial expression.

Identifying the autocorrelation and partial autocorrelation patterns is critical to develop an effective ARIMA model. To select the optimal ARIMA structure, sequentially evaluate models with different parameters to determine the model that best meets the requirements [13].

Figure 6 shows ACF and PACF charts which are useful tools in time series analysis since they help to find parameters for ARIMA models. The ACF graph illustrates the correlation between a time series and its lagged variations, which aids in determining the best order for the moving average (q) parameter by spotting excessive delays when autocorrelation diminishes. Meanwhile, the PACF graph shows a direct correlation between observations at different lags, which assists in estimating the autoregressive (p) parameter. These graphs work together to determine the differencing order (d), which is necessary for achieving stationarity in the time series. Proper parameter selection is crucial in creating successful ARIMA models for time series prediction and analysis.

3.2 SARIMA technique

The SARIMA(p, d, q)(P, D, Q) $_s$ model account for seasonality in time series data, where s denotes the number of seasons in the cycle:

$$\vartheta_p(\beta^s)\vartheta_p(\beta)(1 - \beta)^d(1 - \beta^s)^D S_t = \delta_Q(\beta^s)\theta_q(\beta)\epsilon_t \quad (3)$$

Here: $\vartheta_p(\beta^s) = 1 - \sum_{j=1}^P \vartheta_j \beta^{js}$ and $\delta_Q(\beta^s) = 1 - \sum_{j=1}^Q \delta_j \beta^{js}$. The ARIMA/SARIMA model defines S_t based on previous values and forecast error (ϵ_t) [12].

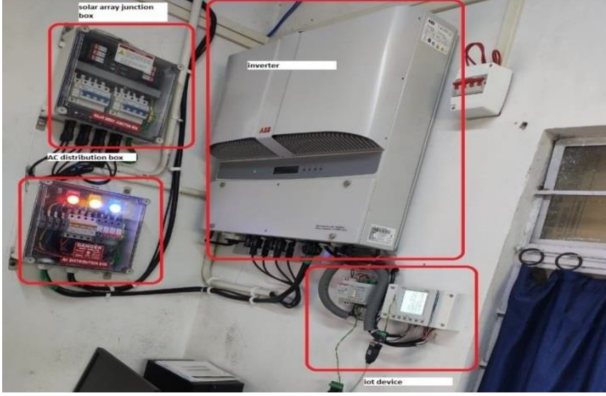


Fig. 7: Real-time IoT setup.

3.3 ETS technique

The fundamental ExponenTial Smoothing (ETS) model has three components: error, trend, and seasonality. The ETS model is commonly labelled as ETS(*, *, *), with the error, trend, and seasonal components listed alphabetically within parentheses. ETS(A, A, A) denotes that the three components are additively related [14]. The model equation for time series S_t is given below:

$$S_t = X'Y_{t-l} + \varepsilon_t \quad (4)$$

$$Y_t = ZY_{t-l} + a\varepsilon_t \quad (5)$$

Here:

$$X = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \quad Z = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad a = \begin{bmatrix} \alpha \\ \sigma \\ \gamma \end{bmatrix},$$

$$Y_t = \begin{bmatrix} l_t \\ b_t \\ s_t \end{bmatrix}, \quad Y_{t-l} = \begin{bmatrix} l_{t-l} \\ b_{t-l} \\ s_{t-l} \end{bmatrix}, \quad l = \begin{bmatrix} 1 \\ 1 \\ s \end{bmatrix}$$

l_t , b_t , and s_t are the level, trend, and seasonal components, respectively. s represents the seasonal period; while α , β , and γ are smoothing constants in above equations.

ETS(M, M, M) is a pure multiplicative variant of ETS(A, A, A) that may be expressed using natural logarithms:

$$\log(S_t) = X' \log(Y_{t-l}) + \log(1 + \varepsilon_t) \quad (6)$$

$$\log(Y_t) = Z \log(Y_{t-l}) + \log(1_n + a\varepsilon_t) \quad (7)$$

In above ETS(M, M, M) equation, 1_n shows the vector of 1's with n elements [15].

3.4 Proposed Technique

The combined ETS model with ARIMA-SARIMA integration provides a solid foundation for time series forecasting. In this hybrid technique, the ETS model preserves the data's fundamental patterns, such as trends and seasonal changes, while ARIMA/SARIMA accounts for any residual autocorrelation structures. The ETS model constantly adapts its components based on the

time series' properties, ensuring long-term adaptation to shifting trends. By combining ARIMA/SARIMA with the ETS model, we take use of the characteristics of both techniques, improving the model's capacity to capture complex temporal dynamics and forecasting accuracy. The combined model incorporates lessons from ETS and SARIMA to provide a comprehensive solution for forecasting energy data.

4. REAL-TIME IOT BASED FORECASTING

IoT has been proposed to monitor the system data and information and communicate the system appliances with the central management system and control unit. The execution time, required memory, and the proposed scheme's time response have been executed to validate the proposed scheme's complexity. The results show the IoT ability to execute the system data and information and respond fast to any system load variations. This improves system performance and avoids the delay in the system energy supply.

Grid-connected mode is one of the decisive and crucial operational modes in microgrid, creates a balance between power generation and consumption to avoid the system outage problem. In this scenario, optimal integration of the microgrid with the traditional grid is solely based on the micro controller unit's decision. Micro controller unit (MCU) decides whether to act as local generation plant or purchase electricity to/from the traditional grid after real-time monitoring and communication with other two control units. One of the other factors that influences the MCU's decision is the worst's case transactional module for the surplus power with the aim to promote business between traditional grid and microgrid. Thus, it is verified that due to transaction mechanism electrical network is always in a balanced state.

Alternatively, the apparent power and PF can be specified. The product of V and I is called the apparent power. The investment cost of a utility depends on the voltage level and the current carried by the conductors. Higher current needs larger, more expensive conductors. Higher voltage means more insulation costs. The revenue of a utility is generally based on the amount of energy in Kilowatt per hour sold. At low power factors, the revenue is low since power P and energy sold is less. For getting full benefit of investment, the utility would like to sell the highest possible energy, that is, operate at unity power factor all the time. Utilities can have a tariff structure that penalizes the customer for low power factor. Most electromagnetic equipment such as motors have low lagging PF and absorb large reactive powers. By connecting capacitors across the terminals of the motor, part or all the reactive power absorbed by the motor can be supplied by the capacitors. The reactive power from the supply will be reduced, and the supply PF improved. Cost of the capacitors is balanced against the savings accrued due to PF improvement.

After following the methodology outlined in the

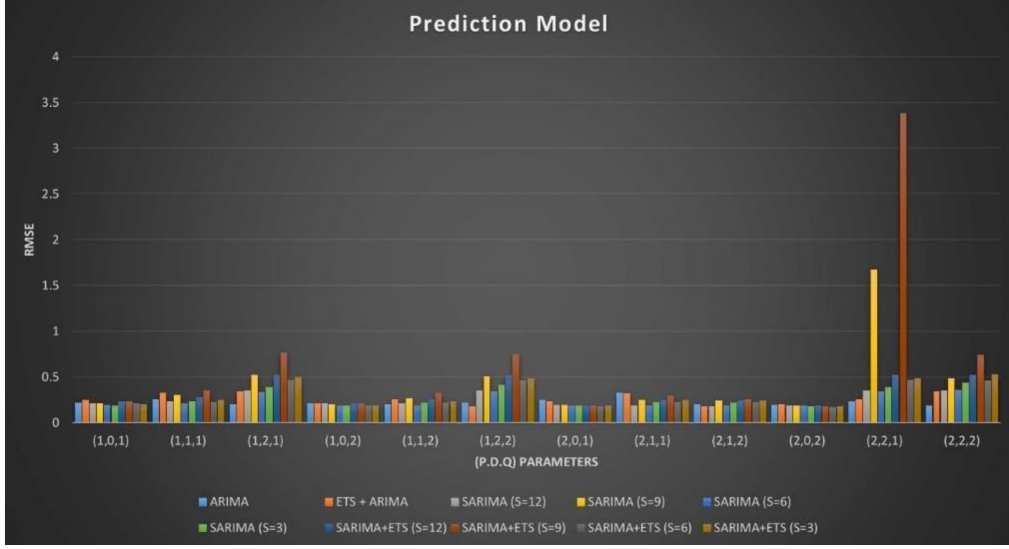


Fig. 8: Bar Chart for RMSE values for several identified models with distinct parameters.

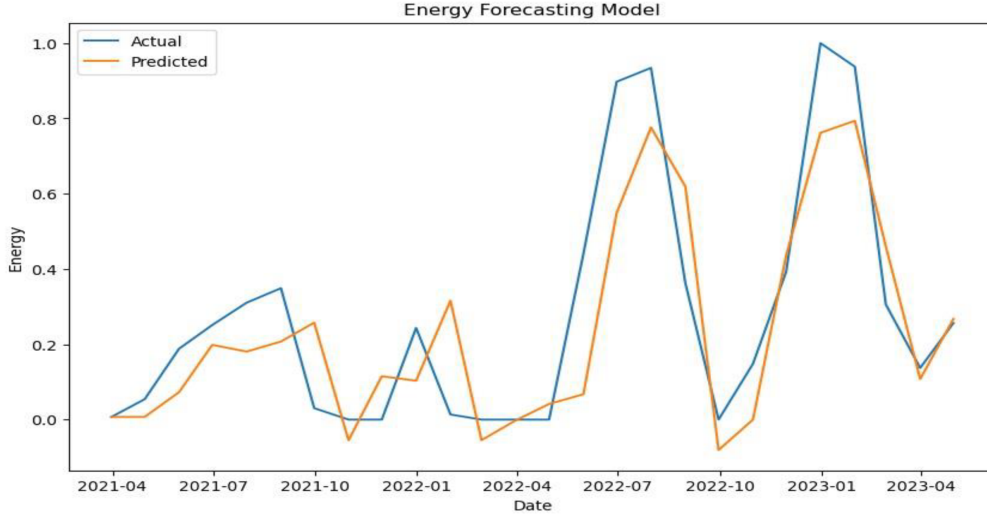


Fig. 9: Energy Forecasting for SARIMA+ETS ($s = 6$) and (p, d, q) as $(2, 0, 2)$.

Data Flow Diagram (DFD) depicted in Figure 5 and selecting parameters based on the chart presented in Figure 6, which depicts ACF and PACF, we obtained Root Mean Squared Error (RMSE) values for various models configured with different parameters. RMSE can be defined as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (S_t - \hat{S}_t)^2} \quad (8)$$

Here: N is the number of data points, S_t is the actual value at time t and $\hat{S}_t$ is the predicted value at time t .

We used individual models as well as combined techniques to improve accuracy, varying parameter combinations. Through this integration, we aim to achieve more accurate and reliable predictions, enabling better-informed decision-making in energy consumption planning and management. The succeeding findings,

along with RMSE values, serve as a standard for assessing model performance. However, it is important to remember that the data was normalized before to analysis.

Table 1 shows RMSE values for several models with different parameters. Columns reflect recognized models (ARIMA, ARIMA+ETS, SARIMA, and SARIMA+ETS), as well as parameters for SARIMA and SARIMA+ETS models such as seasonal orders ($s = 3, 6, 9, 12$). Each row represents the p, d , and q parameters, which we have already examined in ARIMA and SARIMA.

Thresholds for these parameters are determined using the PACF and ACF graphs shown in Fig. 6. Fig. 8 depicts the RMSE distribution for Table 1, which is useful for quickly identifying the top performing parameters and model. Based on the information provided in Table 1 and Fig. 6, we observe that SARIMA+ETS with parameter values $(2, 0, 2, 6)$ for p, d, q , and s respectively perform best with RMSE value 0.1667. However, it

Table 1: RMSE values for several identified models with distinct parameters.

(p, d, q)	ARIM A	ETS+ARIM A	SARIM A (s=12)	SARIM A (s=9)	SARIM A (s=6)	SARIM A (s=3)	SARIMA+ET S (s=12)	SARIMA+ET S (s=9)	SARIMA+ET S (s=6)	SARIMA+ET S (s=3)
(1,0,1)	0.2176	0.2482	0.2088	0.2032	0.1944	0.1878	0.2351	0.2249	0.2089	0.1969
(1,1,1)	0.2576	0.3251	0.2301	0.2967	0.2023	0.2277	0.2752	0.3473	0.2249	0.2453
(1,2,1)	0.2010	0.3411	0.3454	0.5207	0.3339	0.3888	0.5222	0.7575	0.4641	0.4911
(1,0,2)	0.2085	0.2095	0.2032	0.1972	0.1862	0.1853	0.2040	0.2094	0.1817	0.1810
(1,1,2)	0.1988	0.2568	0.2065	0.2661	0.1844	0.2164	0.2583	0.3195	0.2148	0.2270
(1,2,2)	0.2141	0.1759	0.3454	0.5029	0.3373	0.4117	0.5222	0.7453	0.4571	0.4827
(2,0,1)	0.2484	0.2298	0.1925	0.1908	0.1873	0.1856	0.1854	0.1852	0.1725	0.1870
(2,1,1)	0.3250	0.3169	0.1804	0.2457	0.1852	0.2209	0.2448	0.2921	0.2240	0.2437
(2,1,2)	0.2000	0.1752	0.1762	0.2428	0.1864	0.2151	0.2355	0.2565	0.2217	0.2391
(2,0,2)	0.1909	0.1979	0.1831	0.1873	0.1782	0.1737	0.1818	0.1771	0.1667	0.1760
(2,2,1)	0.2310	0.2562	0.3454	1.6725	0.3388	0.3905	0.5222	3.3797	0.4657	0.4832
(2,2,2)	0.1854	0.3374	0.3454	0.4786	0.3535	0.4376	0.5222	0.7428	0.4620	0.5281

Table 2: Heat Map for RMSE values for several identified models with distinct parameters

(p, d, q)	ARIM A	ETS+ARIM A	SARIM A (s=12)	SARIM A (s=9)	SARIM A (s=6)	SARIM A (s=3)	SARIMA+ET S (s=12)	SARIMA+ET S (s=9)	SARIMA+ET S (s=6)	SARIMA+ET S (s=3)
(1,0,1)	0.2176	0.2482	0.2088	0.2032	0.1944	0.1878	0.2351	0.2249	0.2089	0.1969
(1,1,1)	0.2576	0.3251	0.2301	0.2967	0.2023	0.2277	0.2752	0.3473	0.2249	0.2453
(1,2,1)	0.2010	0.3411	0.3454	0.5207	0.3339	0.3888	0.5222	0.7575	0.4641	0.4911
(1,0,2)	0.2085	0.2095	0.2032	0.1972	0.1862	0.1853	0.2040	0.2094	0.1817	0.1810
(1,1,2)	0.1988	0.2568	0.2065	0.2661	0.1844	0.2164	0.2583	0.3195	0.2148	0.2270
(1,2,2)	0.2141	0.1759	0.3454	0.5029	0.3373	0.4117	0.5222	0.7453	0.4571	0.4827
(2,0,1)	0.2484	0.2298	0.1925	0.1908	0.1873	0.1856	0.1854	0.1852	0.1725	0.1870
(2,1,1)	0.3250	0.3169	0.1804	0.2457	0.1852	0.2209	0.2448	0.2921	0.2240	0.2437
(2,1,2)	0.2000	0.1752	0.1762	0.2428	0.1864	0.2151	0.2355	0.2565	0.2217	0.2391
(2,0,2)	0.1909	0.1979	0.1831	0.1873	0.1782	0.1737	0.1818	0.1771	0.1667	0.1760
(2,2,1)	0.2310	0.2562	0.3454	1.6725	0.3388	0.3905	0.5222	3.3797	0.4657	0.4832
(2,2,2)	0.1854	0.3374	0.3454	0.4786	0.3535	0.4376	0.5222	0.7428	0.4620	0.5281

is premature to determine whether this model is the optimal performer. Further evaluation is required to draw conclusive insights.

From Table 1 and Fig. 6, we have identified that the parameter configuration (2, 0, 2) for (p, d, q) consistently yields the best performance. This observation is further supported by the stability of its RMSE value across different scenarios, as depicted in Fig. 8. However, it's essential to ensure that our chosen model, SARIMA + ETS with a seasonal order of 6, provides generalized results. Analysing the performance across various parameters, we observe that this model consistently performs well and maintains stability across different configurations. Therefore, we conclude that SARIMA + ETS with a seasonal order of 6 and parameters (2, 0, 2) for (p, d, q) stands out as the best-performing model, with an RMSE

value of 0.1667.

Fig. 9 illustrates the comparison between the actual and predicted values for the best-performing model, which is SARIMA+ETS with a seasonal order of 6 and parameter configuration (2, 0, 2) for (p, d, q) . With an RMSE value of 0.1667, this model demonstrates stability, as observed in the minimal fluctuations across different scenarios. Based on this stability and consistent performance, we deem this model to be the most reliable and thus consider it the best choice for forecasting.

5. CONCLUSION

In this paper, we have implemented an IoT based real time data forecasting for energy management in solar PV with grid-tied system. Results have been obtained from the experimental set up considering the real time

loads and power from the solar PV. We have observed the total real power is increasing with the irradiation and temperature and the average power factor is almost equal to 1. The total harmonic distortion of voltages and currents of all the phases is below 5%. We can supply the power to grid during the surplus mode which even reduces the burden on the grid. Based on all the results we conclude that the system is a solution for the increasing energy which makes life of easier on this earth.

REFERENCES

- [1] B. E. Sedhom, M. M. El-Saadawi, M. S. El Moursi, M. A. Hassan, and A. A. Eladl, "IoT-based optimal demand side management and control scheme for smart microgrid," *International Journal of Electrical Power & Energy Systems*, vol. 127, p. 106674, 2021.
- [2] H. S. V. S. K. Nunna and D. Srinivasan, "A multi-agent system for energy measurement in smart microgrids with distributed energy storage and demand response," in *2016 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES)*, 2016, pp. 1–5.
- [3] X. Yang, Y. Zhang, and H. He, "Real-time demand side management for a micro-grid considering uncertainties," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, 2019.
- [4] S. Rahim, N. Javaid, and N. Nawaz, "A convex optimization based decentralized real-time energy management model with the optimal integration of microgrid in smart grid," *Journal of Cleaner Production*, vol. 236, 2019.
- [5] N. B. P, J. M. Guerrero, P. Siano, R. Peesapati, and G. Panda, "A novel modified control scheme in grid-tied photovoltaic system for power quality enhancement," *IEEE Transactions on Industrial Electronics*, vol. 68, no. 11, pp. 11100–11110, 2020.
- [6] P. N. Babu, R. Peesapati, and G. Panda, "An adaptive differentiation frequency based advanced reference current generator in grid-tied PV applications," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 8, no. 4, pp. 3502–3515, 2020.
- [7] N. Babu P, J. M. Guerrero, P. Siano, R. Peesapati, and G. Panda, "An improved adaptive control strategy in grid-tied PV system with active power filter for power quality enhancement," *IEEE Systems Journal*, vol. 15, no. 2, pp. 2859–2870, 2021.
- [8] N. Babu P, K. P. Panda, C. B. R. P, and G. Panda, "A novel adaptive fuzzy based controller design using FPGA for grid connected PV systems," in *Advances in Smart Grid Power System: Network, Control and Security*, Elsevier, 2021, pp. 331–364.
- [9] S. Aslam, H. Herodotou, S. M. Mohsin, N. Javaid, N. Ashraf, and S. Aslam, "A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids," *Renewable and Sustainable Energy Reviews*, vol. 144, p. 110992, 2021.
- [10] H. Wang, Z. Lei, X. Zhang, B. Zhou, and J. Peng, "A review of deep learning for renewable energy forecasting," *Energy Conversion and Management*, vol. 198, p. 111799, 2019.
- [11] J. Ma and X. Ma, "A review of forecasting algorithms and energy management strategies for microgrids," *Systems Science & Control Engineering*, vol. 6, no. 1, pp. 237–248, 2018.
- [12] E. Chodakowska, J. Nazarko, Ł. Nazarko, H. S. Rabayah, R. M. Abende, and R. Alawneh, "ARIMA models in solar radiation forecasting in different geographic locations," *Energies*, vol. 16, no. 13, p. 5029, 2023.
- [13] E. Chodakowska, J. Nazarko, and Ł. Nazarko, "ARIMA models in electrical load forecasting and their robustness to noise," *Energies*, vol. 14, no. 23, p. 7952, 2021.
- [14] J. Oh and B. Seong, "Forecasting with a combined model of ETS and ARIMA," *Communications for Statistical Applications and Methods*, vol. 31, no. 1, pp. 143–154, 2024.
- [15] R. Hyndman, A. B. Koehler, J. K. Ord, and R. D. Snyder, *Forecasting with exponential smoothing: the state space approach*. Springer Science & Business Media, 2008.
- [16] N. Babu P, "Adaptive grid-connected inverter control schemes for power quality enrichment in microgrid systems: Past, present, and future perspectives," *Electric Power Systems Research*, vol. 230, p. 110288, 2024.
- [17] N. Babu P, "Power quality enrichment and power management using an adaptive control scheme in microgrid system," *ECTI Transactions on Electrical Engineering, Electronics, and Communications*, vol. 22, no. 3, pp. 1–13, Oct. 2024.
- [18] P. V. S. S. A. Parimala and N. Babu P, "Advanced control and optimization techniques for DFIG wind energy systems: A case study using pelican algorithm and CTID-PID controller," *AIP Advances*, vol. 15, no. 6, p. 065210, Jun. 2025.



Narendrababu P received the Ph.D. and M.Tech degrees in Power and Energy Systems specialization from the National Institute of Technology (NIT) Meghalaya, Shillong, in 2022 and 2017, respectively. He received the B.Tech. degree in Electrical and Electronics Engineering (EEE) from Jawaharlal Nehru Technological University Hyderabad, Hyderabad, India in 2010. He has as a research experience of 4 years as a Senior Research Fellow with RECTPCL-CSR Funded Project during 2017-2021, Department of Electrical Engineering, National Institute of Technology Meghalaya and 4.9 years of industry experience as an Assistant Electrical Engineer at JSK Lab during 2010-2015. He has published more than 35 research publications in IEEE Transactions, Wiley, Elsevier, Taylor and Francis, and reputed international Conferences with high impact factors. He has published 7 book chapter in Elsevier and others. He received more than 750 Google scholar citations with 15 H-index and 19 i-10 index. Moreover, he has been listed in the world's top 2% scientists produced by Stanford University and Elsevier in 2025. Presently, he is working as an Assistant Professor Senior G-1 in the School of EEE at VIT Bhopal University from 2021 to till date. His current research interests include renewable energy technologies, hybrid ac-dc microgrid, power quality, adaptive control, EV technologies, and control of grid-tied inverters.



Dadinaboina Anantha Koteswara Rao received the B.Tech. degree in electrical and electronics engineering from VR Siddhartha Engineering College, Vijayawada, India, and the M.E. degree in power systems & Automation specialization from Andhra University, Visakhapatnam India, in 2010 and 2014, respectively. I am Working as an Assistant Professor in SRKR Engineering College, Bhimavaram, AP, India. He received Ph.D. degree in Annamalai University Faculty of

Engineering and Technology in the Department of Electrical Engineering, Chidambaram, India from 2018 to till date. My current research interests include renewable energy technologies, hybrid ac-dc Microgrid, Power Quality and control of grid-tied inverters.